METAHEURISTICS BASED ON GENETIC ALGORITHM AND TABU SEARCH FOR VEHICLE ROUTING PROBLEM WITH STOCHASTIC DEMANDS

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To those that have affected my life in the most wondrous way:

My husband Hendro Nurhadi,
My daughter Hana Azizah Nurhadi,
My mother and father Alm. Noor Hidayati and Ali Muhayin,
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ABSTRACT

This study considers a Vehicle Routing Problem with Stochastic Demands (VRPSD) where the demands are unknown when the route plan is designed. The VRPSD objective is to find an *a priori* route under preventive restocking that minimizes the total expected cost, subject to the routing constraints, under the stochastic demands setting. Various metaheuristics based on Genetic Algorithm (GA) and Tabu Search (TS) were proposed to solve VRPSD. This study began with investigating the effect of static and dynamic tabu list size in TS. The results showed the advantage of dynamic tabu list size in significantly reducing the probability of cycling. Further, Reactive Tabu Search (RTS) which has never been used in VRPSD was introduced. This study showed that RTS give significant improvement to the solution quality of TS. This study then explored the enhancement of GA for VRPSD by proposing Adaptive GA (AGA), Breeder GA (BGA) and two types of Hybrid GA with Tabu Search (HGATS). Solutions generated using AGA were better than solutions from fixed parameter setting, and the use of AGA reduce the amount of time required in finding the appropriate mutation probability values of GA. The BGA also gave an improvement to the solution quality of GA. Different schemes of incorporating TS to GA lead to a significantly different performance of the HGATS algorithms. Next, comparative studies between metaheuristics implemented in this study were carried out including the comparison with previous research on GA for VRPSD. The HGATS showed superiority in terms of solution quality compared to other metaheuristics, followed by BGA and RTS in the second and third best performance respectively. Furthermore, the proposed bi-objective Pareto BGA gave better solution qualities compared to Pareto GA. Finally, the use of metaheuristics in a case study of solid waste collection reduced significantly the company current operation cost.

ABSTRAK

Kajian ini mempertimbangkan suatu Masalah Perjalanan Kenderaan bersama Permintaan Stokastik (VRPSD) di mana permintaan tidak diketahui ketika perancangan laluan dibuat. Objektif VRPSD adalah untuk menentukan suatu perjalanan *a priori* di bawah pencegahan stok semula bagi mengurangkan jumlah kos jangkaan, bergantung kepada kekangan perjalanan dengan permintaan stokastik. Pelbagai metaheuristik berasaskan Algoritma Genetik (GA) dan Carian Tabu (TS) telah dicadangkan untuk menyelesaikan masalah tersebut. Kajian ini bermula dengan menyelidik kesan statik dan dinamik saiz senarai tabu di dalam TS. Hasil kajian menunjukkan kebaikan saiz senarai tabu dinamik telah berupaya mengurangkan dengan signifikan kebarangkalian kitaran. Seterusnya *Reactive Tabu Search* (RTS) yang belum pernah digunakan dalam VRPSD diperkenalkan di mana ia menunjukkan RTS mempertingkatkan kualiti penyelesaian TS. Kajian ini seterusnya menerokai peningkatan GA untuk VRPSD dengan mencadangkan *Adaptive GA* (AGA), *Breeder GA* (BGA) dan dua jenis *Hybrid GA-Tabu Search* (HGATS). Penyelesaian yang dihasilkan AGA adalah lebih baik berbanding penggunaan parameter tetap dan dengan menggunakan AGA, jumlah masa yang diperlukan untuk mencari kebarangkalian nilai mutasi GA yang sesuai juga boleh dikurangkan. Kaedah BGA juga meningkatkan kualiti penyelesaian GA. Skema berlainan dalam menggabungkan TS dengan GA membawa kepada perubahan pencapaian algoritma HGATS. Seterusnya kajian perbandingan di antara metaheuristik yang dilaksanakan di dalam kajian ini dilakukan termasuk perbandingan dengan kajian terdahulu tentang GA untuk VRPSD. HGATS yang dicadangkan, menunjukan keunggulan berbanding yang lain, diikuti oleh BGA dan RTS di tempat kedua dan ketiga pada tahap pencapaian. Seterusnya Pareto BGA yang dicadangkan untuk menyelesaikan dua-objektif VRPSD telah menghasilkan penyelesaian yang lebih baik berbanding Pareto GA. Akhirnya, penggunaan metaheuristik dalam satu kajian kes pengangkutan bahan buangan pepejal didapati mengurangkan dengan signifikan kos operasi semasa syarikat.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Optimisation is a part of life. In our day to day lives, we make decisions that we believe can maximize or minimize our objectives, such as taking a shortcut to minimize the time or distance required to reach a particular destination, or finding a lowest priced items in the supermarket. Most of these decisions are based on our years of experience and knowledge about the system without resorting to any systematic mathematical formulation. However, as the system becomes more complicated, further it is needed to formulate it into specific mathematical model, and with the advent of computer it is possible to exploit optimisation theories to their maximum extent.

Combinatorial optimisation is a branch of optimisation that arises everywhere and certainly in applied mathematics and computer science, related to operations research, algorithm theory and computational complexity theory that sit at the intersection of several fields, including artificial intelligence, mathematics and software engineering. Combinatorial optimisation algorithms solve problem instances that are believed to be hard in general, by exploring the usually large solution space of these instances. Combinatorial optimisation algorithms achieve this by reducing the effective size of the space and by exploring the space efficiently. The Vehicle Routing Problems (VRP), Traveling Salesman Problem (TSP), minimum spanning tree problem and knapsack problem are examples of combinatorial optimisation problem.

Since late fifties, the Vehicle Routing Problem (VRP) has been and remains a rich topic for researchers and practitioners. It becomes an area of importance to operations research as well as its use for many real world applications. An integral component of logistics is transportation, and a frequently arising situation in the transportation and distribution of commodities has usually been modeled as a Vehicle Routing Problem (VRP). Usually real world VRP arises with many site constraints. VRP is a generalized problem of the Traveling Salesman Problem (TSP) in that the VRP consists in determining *m* vehicle, where a route is tour that begins at the depot. The task is to visit a set of customer in a given order and returns to the depot. All customers must be visited exactly once and the total customer demand of a route must not exceed the vehicle capacity. Given a set of geographically dispersed customers, each showing a positive demand for a given commodity, the VRP consists of finding a set of tours of minimum length (or cost) for a fleet of vehicles. According to Secomandi (2003), the class of VRPs is a difficult one, since its elements are usually NP-hard problems and they are generally solved by heuristic methods. Lenstra and Kan (1981) has shown that VRP is NP-hard problem.

The majority of these researches conducted on operations research are focus on static and deterministic cases of vehicle routing in which all information is determined before the time of planning the routes. Whereas in this ICT age, information is gathered in real time and in many cases they are changing. The complexity of the problem increases as more information is unavailable at the time of the planning or when the service has begun such as the time to begin service, the location and the actual demand. In most real life application, stochastic or dynamic information occurs parallel to the routes being carried out. Many of the vehicle routing problems have inherent randomness, which is not considered in deterministic models, probably travel times or demands are random variables with known distributions. Tillman (1969) started the works to explore cases on VRP with stochastic demands. Since that, many theories and algorithms on VRPSD have been proposed and or developed. In this research, we are interested in studying the demand as the stochastic component.

This chapter presents the flow of the research proposal and it begins with the background and problem statement of the research. It is important that an extensive work has been carried out in order to present a case for this work and this is given in Chapter 2. Research objectives, the scope of this study and discussion on the research contribution are also given. Finally, the brief of each chapter is outlined.

1.2 Background of the problem

The classical VRP models usually do not capture an important aspect of real life transportation and distribution-logistic problems, namely the fact that several of the problem parameters (demand, time, distance, city location, etc) are often stochastic. Most existing VRP models oversimplify the actual system by assuming system parameter (e.g. customer demands) as deterministic value, although in real application, it may not be possible to know all information about customers before designing routes. Stochastic information occurs and has major impact on how the problem is formulated and how the solution is implemented. Neglecting the stochastic nature of the parameters in a vehicle routing model may generate sub optimal or even infeasible routes (Yang *et al*., 2000).

As compared to the development in deterministic case, research in Stochastic VRP is rather undeveloped. Gendreau *et al.* (1996) summarise the solution concepts and literature available on different kinds of SVRP including the TSP with stochastic customers, the TSP with stochastic travel times, the VRP with stochastic demands, the VRP with stochastic customers and the VRP with stochastic customers and demands. Stochastic VRP cannot be solved as VRP since properties and the optimal VRP solution do not hold for the SVRP (Dror *et al*., 1989). Further, it calls for more complex solution methodologies (Gendreau *et al.*, 1995).

This study focus on VRP with Stochastic Demands (VRPSD) in which demand at each location is unknown at the time when the route is designed, but is follow a known probability distribution. This situation arises in practice when whenever a company, on any given day, is faced with the problem of collection/

deliveries from or to a set of customers, each has a random demand. In this study, we deal with specific case on solid waste collection. It is hoped that optimisation can take into account the stochasticity of the problem in obtaining better routes and reducing cost.

In stochastic environment, due to its randomness in customers' demands, a vehicle capacity may be exceeded during service. A route failure is said to occur if the demand exceeds capacity and a recourse action needs to be taken at extra cost. Assuming that enough capacity is available at the depot, the vehicle may return to the depot, replenish its load, and then resume service at the point where failure occurred. Therefore the vehicle will always be able to satisfy all demands but the length of the corresponding tour becomes a random quantity.

The recourse action could be the vehicle resumes service along the planned route, namely *a priori* approach, or visiting the remaining customers possibly in an order that differs from the planned sequence known as *re-optimisation* approach. There are two common recourse policies for a priori optimisation. The first is the simple recourse policy (Dror *et al.*, 1989; Gendreau *et al.*, 1995; Chepuri and Homem-de-Mello, 2005) where a vehicle returns to the depot to restock when its capacity becomes attained or exceeded. The second approach is the preventive restocking (Bertsimas *et al.*, 1995; Yang *et al.*, 2000; Bianchi *et al.*, 2004) where preventive restocking is planned at strategic points preferably when the vehicle is near to the depot and its capacity is almost empty, along the scheduled route instead of waiting for route failure to occur. On the other hand, most recent computational studies in *re-optimisation* approach were done by Secomandi (2000, 2001, 2003).

In this study, we use a priori approach since redesign the routes when actual demand becomes known appears to be a problem for several reasons:

1. Resources might not be available.
2. Even if resources are available, it might be that redesign of routes is not sufficiently important to justify the required effort, cost and time.
3. Redesigning the route might create confusing to the driver.

4. Regularity and personalization of service by having the same vehicle and driver visit a particular customer every day is not guaranteed if one redesigns the routes.

For our case in solid waste collection, familiarity of driver and waste collector on the route visited every day is highly emphasized; usually the route is substantially not changed. Redesign the routes might cause a problem in the situation when demand is highly variable, thus the routes could be different each day, creating route instability which has consequences to system nervousness in material requirements planning. Further, if demand is stable, it still requires the company personnel to understand day by day task of gathering and inputting new demand to algorithm that generate routes and then deliver the output information to driver.

Tillman (1969) was the first to propose algorithm for the VRPSD in the case where there were multiple terminal deliveries and multiple vehicles. Since then, many researchers have studied this problem in two frameworks, namely the chance constrained and stochastic with recourse. In the chance constrained VRPSD, the problem is to design a number of vehicle routes of least distance traveled, subject to the constraint that the probability of route failure on any route is within an allowable limit. In contrast, VRPSD with recourse try to minimize the total expected cost (or distance), including the cost of travel as well as the cost of recourse action when a route failure occurs. The VRPSD with recourse is considerably more difficult than chance constrained VRPSD (Gendreau *et al*., 1995).

Various formulations and algorithms have been proposed and investigated, including the properties and solution frameworks of VRPSD studied by Dror *et al.* (1989), Bertsimas (1992) who proposed cyclic heuristic and found a priori solution for single vehicle and Dror *et al.* (1993) who have examined a priori VRPSD in the context of Stochastic Programming where there is only one vehicle and the number of potential failures is small. Yang *et al.* (2000) developed optimal restocking policy in conjunction with routing decisions for a priori VRPSD for single and multiple vehicles. Secomandi (2001, 2003) considered re-optimisation-type routing policy by means of rollout policy for single vehicle.

Bianchi *et al.* (2004) considered basic implementation of five metaheuristics for single vehicle: Iterated Local Search, Tabu Search, Simulated Annealing, Ant Colony Optimisation and Evolutionary Algorithm (Genetic Algorithm) that found better solution quality in respect to cyclic heuristic. Chepuri and Homem-de-Mello (2005) proposed a new heuristic method based on the Cross-Entropy method for single vehicle. Instead of the work of Bianchi *et al.* (2004) and Gendreau *et al.* (1995), the work on the application of GA and TS for VRPSD are lacking in the literature. The work of Bianchi *et al.* (2004) results that the performance of GA and TS seem to be not significantly different, due to the fact that these algorithms find solutions values which are not very different to each other, but can not compete ILS.

These facts have opened a new direction to conduct research on GA and TS for solving VRPSD. Moreover, it is widely known that GA has been proven effective and successful in a wide variety of combinatorial optimisation problems, including TSP and certain types of VRP, especially where time windows are included. TS, the approach that dominates the list of successful algorithms, is known also as a robust, efficient and effective approach to the general VRP family of problem (Laporte, 1992; Osman, 1993). TS often outperform other heuristic techniques in terms of computational speed and solution quality (Osman, 1993).

The number of published work on the application of GA for solving basic VRP, TSP, VRPTW, VRPB, and multi depot VRP has been growing. Different approaches were also proposed based on different crossover operator, different mutation operator, or replacement methods. Although pure GA performs well, mostly it does not equal TS in terms of solution quality, sometimes pure GA perform inefficient on practical combinatorial optimisation. To improve pure GA performance, some algorithms are combined with the simple GA, yielding a hybrid algorithm.

The statement about GA hybridization is noted by Coley (1999) that hybrid algorithms, which combine a GA with more traditional algorithms, have been hinted as a highly powerful combination for solving practical problem, also by Lacomme *et al.* (2006) that it is well known that a standard GA must be hybridized with another search procedure to be able to compete with metaheuristics like TS. Baker and

Ayechew (2003) showed that hybrid GA with neighbourhood search in the basic VRP is competitive with TS and SA in terms of solution time and quality. Hybrid GAs also have widespread application to VRPTW, including the work of Blanton and Wainwright (1993), Thangiah (1995a and 1995b), Berger *et al.* (1998) and Braysy *et al.* (2000).

Based on previous research on algorithms developed for VRPSD and the knowledge of the basic structure of GA and TS, in this study we develop metaheuristics based on GA and TS as the enhancement of basic GA and TS for solving single and multiple VRPSD in minimizing single objective function. Our reviews also found that hybrid GA has not been used to solve VRPSD and most of researches in VRPSD with preventive restocking are dealing with single VRPSD and little work has been done for multiple VRPSD, even though decisions relating to routing fleets of vehicles are frequently taken into consideration in distribution and logistics operations. This brings us to also develop the meta-heuristics based on hybrid GA and TS to solve a priori VRPSD comprises single vehicle and multiple vehicles.

The approach developed was inspired also by the emerging interest in hybrid metaheuristics that has risen considerably among researchers in combinatorial optimisation. The best results found for many practical or academic optimisation problems are obtained by hybrid algorithms (Talbi, 2002). In this study, the GA will be hybridized with TS. It is highly expected that this hybrid could combine the advantage of GA as population-based method and the strength of TS as trajectory method. As known, population-based methods are better in identifying promising areas in the search space, whereas trajectory methods are better in exploring promising areas in search space.

In this study, we also propose metaheuristics for solving bi-objective VRPSD to minimize the total expected cost and the number of vehicles. This study is motivated by fact that many real world design or decision making problems involve simultaneous optimisation of multiple objectives (Srinivas and Deb, 1994). But most of the existing literatures in VRPSD, except of multi-objective's Tan *et al.* (2007), use single-objective based heuristics. In a single-objective optimisation, the main goal is to find the global optimum solution. However, in a multi-criterion optimisation problem, there are more than one objective function, each of which may have different individual optimal solution. If there is sufficient difference in the optimal solutions corresponding to different objectives, the objective functions are often conflict each other. Multi-criterion optimisation with such conflicting objective functions gives rise to as set of optimal solutions, instead of one optimal solution. The reason for the optimality of many solutions is that none can be considered to be better than any other with respect to all objectives.

1.3 Problem Statement of Research

The VRPSD is defined on a complete graph $G = (V, A, C)$, where

V = $\{0, 1, \ldots, n\}$ is a set of nodes with node 0 denotes the depot and nodes 1, 2, …, n correspond to the customers,

A = $\{(i, j) : i, j \in V, i \neq j\}$ is the set of arcs joining the nodes, and

C = $(c_{ij} : i, j \in V, i \neq j\})$ is a non-negative matrix (a matrix where all the elements are equal to or above zero, $C \geq 0, \forall (i, j), c_{ij} \geq 0$) that denotes the travel cost (distance) between node i and j.

The cost matrix C is symmetric and satisfies the triangular inequality. Customers have stochastic demands ξ_i, $i = 1, \ldots, n$, which are a non-negative discrete random variable with known probability distribution $p_{ik} = \Pr ob(\xi_i = k)$, $k = 0, 1, \ldots, K \leq Q$. Assume further that customers' demands are independent and identical. Actual demand is only known after the vehicle arrives at customer's location. If there is a route failure at any node, the recourse action has to be taken, the recourse action is to travel back to the depot for replenish and then resume its journey as planned at the node where failure occurred. The problem objective is to find a priori routes that minimize the total expected cost, including travel cost and the expected recourse cost, subject to the routing constraints, under the stochastic demands setting.

A stochastic vehicle routing problem arises when not all information relevant to the planning of the routes is known by the planner when the routing process begins and information can change after the initial routes have been constructed. According to Secomandi (2003), for the class of deterministic VRPs, they are generally solved by heuristic or metaheuristic methods; whereas algorithms for stochastic VRP are considerably more intricate than deterministic and it calls for efficient algorithm that is able to work in real-time since the immediate requests should be served. These have made them an important candidate for solution using metaheuristics.

This research tries to propose new metaheuristics based on GA and TS to enhance the performance of basic GA and basic TS for solving VRPSD. In this work, we initially consider a single-vehicle model and later expand the analysis to incorporate multiple vehicles. We also develop metaheuristics for solving bi-objective VRPSD. The performances of the proposed algorithms were compared each other and with other heuristics/ metaheuristics. The implementation of these algorithms also will be done to solve real problem in optimizing solid waste collection.

1.4 Objectives of the Study

The aim of this study is to develop various approaches to optimize VRPSD solution, particularly in the use of metaheuristics approach. The objectives of this study are to:

- develop metaheuristics for solving single VRPSD that include:
    a. Tabu Search and Reactive Tabu Search.
    b. Genetic Algorithm and the enhanced GA, i.e. :
        - Adaptive Genetic Algorithm
        - Breeder Genetic Algorithm and
        - Hybrid GA and TS

- develop GA-based metaheuristic for solving bi-objective multiple VRPSD.
- conduct comparative evaluation on the performance among these metaheuristics.
- solving real problem data in optimizing solid waste collection by using the VRPSD model and the developed metaheuristics.

1.5 Scope of the Study

1. In this research, we confine the application of our algorithm to a priori VRPSD under restocking policy.
2. The problem data for the performance testing in simulation study are randomly generated problem data following specific probability distributions.
3. We confine our real problem solving in the case study of optimizing solid waste collection.
4. It is assumed that vehicles start and end at a single depot.
5. It is assumed that every customer demands have the same probability distribution but can have different parameters (for example: different mean and variance for each customer that have normal distribution).
6. The problem data were generated using Minitab version 14 and were tested and analyzed using SPSS version 13 for Windows, while the implementation of metaheuristics was done using Delphi version 6.0. Minitab has special feature in generating random data following specific probability distribution which SPSS does not have, while SPSS has advantage in better graphical representation of the output of data analysis than Minitab.
7. The stopping criteria in addressing convergence for all procedures presented in this study will not using numerical analysis component/ complexity analysis.

1.6 Significance of the Study

1. From the view point of algorithm development: our algorithms are the first implementation of
    - Reactive Tabu Search,
    - Adaptive GA,
    - Breeder GA,
    - and hybrid GA (especially hybrid GA with Tabu Search)

   for solving single and multiple vehicles appeared in the VRPSD literature.
2. We also propose the new adaptive mutation probability measure.
3. We contribute on the first considering bi-objective VRPSD under restocking policy and proposing new GA-based for solving bi-objective multiple VRPSD.
4. From application aspect, real problem in optimizing waste collection was solved by using the proposed algorithm.
5. We also develop software package for solving VRPSD.
6. And the result of this study will be presented and published at the international publications/ journal.

Along the recent increase in the demand for an efficient management system for VRP and logistics and the advances in computer and information technology, the importance of being able to effectively make use of the huge amount of information has become important for a wide range of applications. Cost efficient routing of vehicles play an important role to a wide range of industries. As indicated earlier, our focus would be to work on the problem related to VRP for solid waste collection in the Municipality of the Johor Bahru city.

1.7 Organisation of the Thesis

This thesis contains eight chapters. The first chapter is the introduction. This chapter gives an introduction to the background of the problem, the statement of the problem, objectives and scope of the study, and significance of the study.

Chapter two is the Literature Review. This chapter presents a literature review about the Vehicle Routing Problem with Stochastic Demands, solution techniques appeared in literature and also techniques which may be applied for solving VRPSD.

Chapter three is the Research Methodology. This chapter presents the direction of the study and an overview of the methods used. It begins with the general steps of research framework. A description of the data source for this study and test related to it are also presented include case-study of a real-life application at solid waste collection company (Perniagaan Zawiyah Sdn. Bhd). It follows with the description of algorithm implemented with emphasis on Genetic Algorithm, Tabu Search and the enhancement of these two metaheuristics.

In Chapter four, the development of metaheuristic methods based on Tabu Search and Reactive Tabu Search for solving single VRPSD are explored. The discussion of this chapter begins with the detail development of Tabu Search and Reactive Tabu Search for single VRPSD, followed by the experimental results and discussion.

Chapter five discusses the development of several Genetic Agorithm-based metaheuristics for solving single VRPSD. The standard Genetic Algorithm is presented, followed by the enhancement of it through Adaptive Genetic Algorithm, hybrid Genetic Algorithm with Tabu Search, and the Breeder Genetic Algorithm.

Chapter six considers multiple VRPSD which analog of the deterministic VRP. The use of Breeder Genetic Algorithm is proposed to solve the bi-objective VRPSD in minimizing the number of vehicles required and the total expected cost concurrently, using Pareto-rank by modifying and extending the single-objective Breeder Genetic Algorithm.

VRPSD finds its application on wide range of logistics and distribution sector in cases where it is impossible to know the demand of the customers before the vehicles arrives at customer's location. In Chapter seven, the implementation of

VRPSD in the case of picking up of garbage done by solid waste company in Johor Bahru namely Perniagaan Zawiyah Sdn. Bhd. is discussed.

Finally, Chapter eight concludes the relevant and important findings from this research. Recommendations on area related to the findings and possible directions for future research are presented.

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